

Pushing the limits of BCI accuracy: Winning solution of the Grasp & Lift EEG challenge.

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Introduction

To better understand the relationship between EEG signals and hand movements the WAY Consortium has organized the Grasp-and-Lift EEG Detection challenge. It was held in 2015 from 29th June to 31th August on Kaggle, a platform for competitive predictive modeling, and attracted 379 contesting teams. The goal of the challenge was to detect 6 different events related to hand movement during a task of grasping and lifting an object, using only EEG signal. This poster presents the winning solution of this challenge.

The Competition

Goal : Detection of 6 events corresponding to a sequence of hand movements during a task consisting of grasping and lifting an object. Events are 300ms wide and are extracted from EMG signal.



Dataset : 32 EEG channels, 500 Hz, 12 subjects. 10 series of 30 trials per subject. First 8 series formed a training set, the 9th series a validation set, and the last one a test set. The dataset is publicly available [1].

Task : Contestants were asked to provide detection probabilities for the 6 events and for *every time sample* for both validation and test sets. The model must be causal.

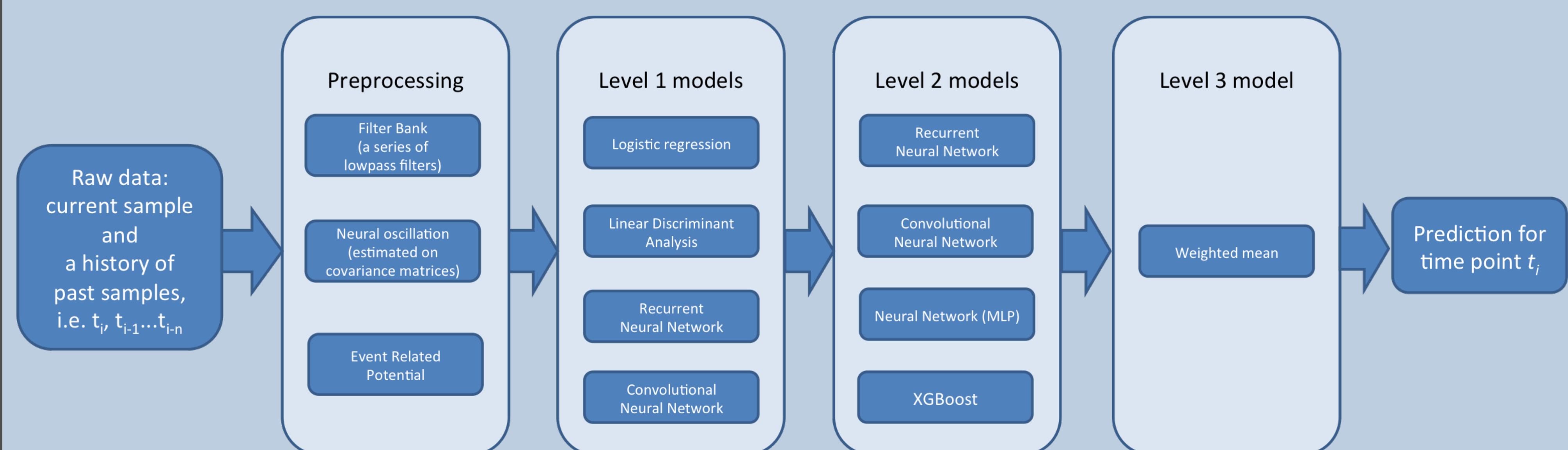
Evaluation : Average AUC of the 6 events on the test set.

A challenging problem

In many ways, the formulation of the problem differed from a typical motor imagery BCI problem:

1. The 6 events represented different stages of a sequence of hand movements and therefore the temporal structure of the sequence had to be taken into account. Some events were overlapping, and some others were mutually exclusive.
2. Events to detect were short timed (300ms) and positive predictions have to be provided for the entire frame. The sharpness of the prediction was critical for achieving optimal accuracy.
3. Predictions have to be provided for every time sample (3 million in total), which represents a considerable amount of data.

The Solution : A 3-level classification pipeline.



- Level1 models are subject-specific, i.e. trained independently on each subject. Most of them are also event-specific. Their main goal is to provide support and diversity for level2 models by embedding subject and events specificities using different types of features. A total of 51 level1 models were developed.
- Level2 models are global models (i.e. not subject-specific) that are trained on level1 predictions (metafeatures). Their main goal is to take into account the temporal structure and relationship between events. As a by-product, global models significantly helps to calibrate predictions between subjects. 32 level2 models were used.
- Level3 models ensemble level2 predictions with weighted average, where weights are optimized to maximize AUC of the ensemble. This step improves the sharpness of predictions while reducing overfitting.

Results

- **Level1** models were built on a wide range of different features: Time domain EEG signal filtered by a bank of low-pass filters (0.5, 1, 2, 3, 4, 5, 7, 9, 15, 30 Hz), Riemannian distance of covariances matrices [2] in different frequency bands or special form ERP covariance matrices [3]. The best level1 model was a convolutional neural network and achieved 0.95 AUC.
- **Level2** models were ensembling predictions of level1 models using non-linear classifiers. The best being a recurrent neural network that achieved 0.98 AUC.
- **The final model** was a weighted average of level2 prediction and scored 0.981 AUC, allowing our team to take the first position of this challenge.

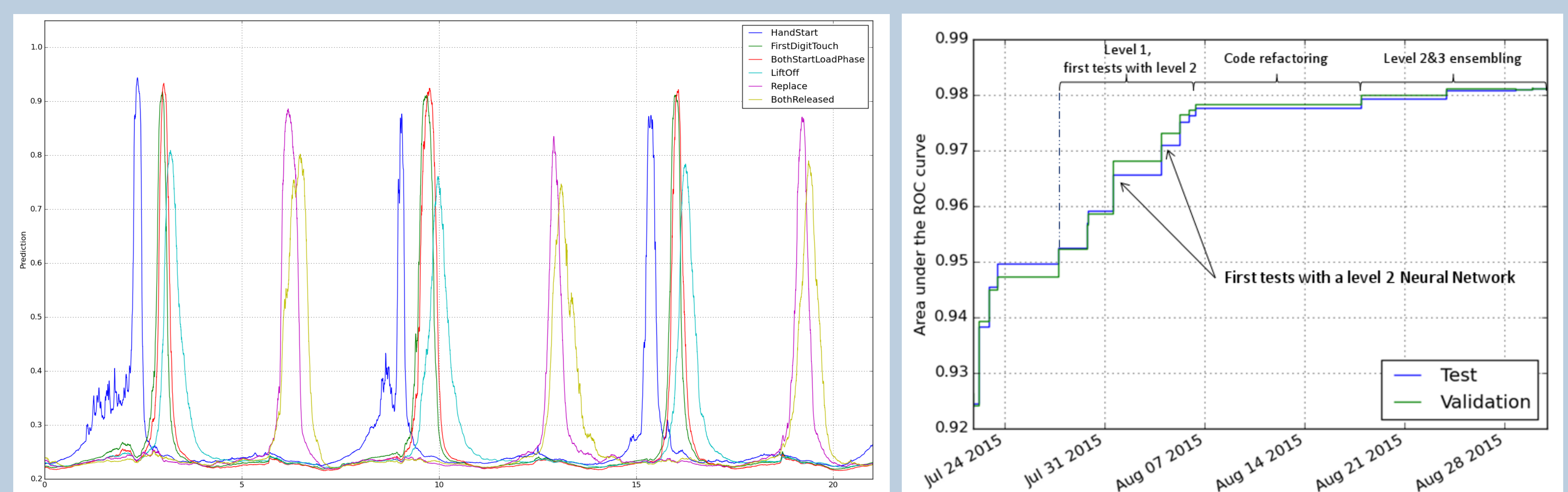


Figure 1: Output probabilities of the model (left); Score progression across the competition (right)

Team	Score (AUC)
1st - A. Barachant; R. Cycon	0.98109
2nd - M. Liang	0.98029
3rd - T. Hochberg; E. Bekele; E. Cuoco; J. Fan	0.97996

Table 1: Final standing of the challenge

References

- [1] M. D. Luciw, E. Jarocka, and B. B. Edin. Multi-channel eeg recordings during 3,936 grasp and lift trials with varying weight and friction. *Scientific data*, 1, 2014.
- [2] A. Barachant, S. Bonnet, M. Congedo, and C. Jutten. Multi-class brain computer interface classification by riemannian geometry. *Biomedical Engineering, IEEE Transactions on*, 59(4):920–928, 2012.
- [3] A. Barachant and M. Congedo. A plug&play p300 bci using information geometry. *arXiv preprint arXiv:1409.0107*, 2014.

Conclusion & Discussion

- With an atypical problem formulation, state of the art motor imagery pipeline (CSP + LDA, etc) were not adapted and scored poorly (0.7 AUC). The key was to take into account the temporal structure of the sequence of events.
- With different level of ensembling it is possible to significantly boost accuracy beyond what a single model can achieve (at the cost of system complexity).
- Very high quality of the EEG signal and precise event tagging allowed to successfully apply highly nonlinear models such as neural networks.